Comparison of Wiener and Inverse Filtering on Degraded Images

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Abstract

This project explores the performance of Wiener and Inverse filtering methods for image restoration. We used a set of medical images from a Kaggle dataset, artificially degraded them with blur and noise, and then applied both filtering techniques. The restored images were evaluated using PSNR, SSIM, and MSE.

1 Introduction

Motion blur is a common form of image degradation, caused by relative movement between the camera and the scene during the exposure time. Such blur reduces the visibility of fine details and edges, significantly affecting image quality and the ability to extract meaningful information. In many real-world applications—including photography, surveillance, and medical imaging—restoring the original sharp image is essential for accurate interpretation and analysis.

This project investigates the restoration (deblurring) of motion-blurred images using two classical frequency-domain methods: **Inverse Filtering** and **Wiener Filtering**. Both methods rely on modeling the degradation process as a convolution between the original image and a Point Spread Function (PSF), which represents the motion blur kernel. By estimating or knowing the PSF, the original image can be approximately recovered.

Through this project, we aim to demonstrate the strengths and limitations of classical frequency-domain deblurring methods. While inverse filtering provides a direct but noise-sensitive approach, Wiener filtering offers a more robust balance between blur removal and noise suppression. This comparative analysis highlights how such methods can be applied to challenging domains like medical imaging, where image quality directly impacts diagnostic accuracy.

2 Dataset and Preprocessing

We selected several medical images from a public Kaggle dataset and artificially degraded them to simulate realistic imaging conditions. Each image was blurred using a known kernel (such as motion blur or Gaussian blur), and additive Gaussian noise was introduced to replicate real-world degradation. We then applied both Inverse and Wiener filters to restore these degraded images and evaluate the effectiveness of the two methods.

3 Evaluation Metrics

To quantitatively evaluate the performance of image restoration methods, we employed three widely used metrics: **Peak Signal-to-Noise Ratio (PSNR)**, **Structural Similarity Index (SSIM)**, and **Mean Squared Error (MSE)**. Each of these metrics provides a different perspective on image quality and the similarity between the restored image and the reference (original) image.

3.1 Peak Signal-to-Noise Ratio

PSNR is a logarithmic metric that measures the ratio between the maximum possible pixel intensity (signal) and the distortion (noise) introduced by restoration. It is defined as:

$$PSNR = 10 \cdot \log_{10}(\frac{MAX_I^2}{MSE})$$

where MAX_I is the maximum possible pixel value (e.g., 255 for 8-bit images). A higher PSNR value generally indicates better restoration quality, as it means the restored image is closer to the original. However, PSNR does not always correlate well with perceived visual quality, especially for images with structural distortions.

3.2 Structural Similarity Index

SSIM is a perceptual metric that compares the structural information, luminance, and contrast between two images. It is designed to mimic the human visual system's sensitivity to structure. SSIM values range from -1 to 1, where 1 indicates perfect similarity:

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

where μ_x and μ_y are the mean values of the images, σ_x^2 and σ_y^2 are variances and σ_{xy} is the covariance. SSIM is particularly important in **medical imaging**, where structural details are critical for diagnosis.

3.3 Mean Squared Error

MSE measures the average squared difference between the pixels of the original and restored images:

$$\text{MSE} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} [I(i, j) - K(i, j)]^2$$

where I is the original image and K is the restored image of size $M \times N$. A lower MSE value indicates better restoration quality. Although simple, MSE is sensitive to large errors but does not reflect perceptual quality as effectively as SSIM.

4 Methodology

4.1 Inverse Filtering

Inverse filtering attempts to reverse the blurring operation in the frequency domain, assuming the blur kernel is known:

$$F(u, v) = \frac{G(u, v)}{H(u, v)}$$

where $G(u, v)$ is the degraded image and $H(u, v)$ is the blur function.

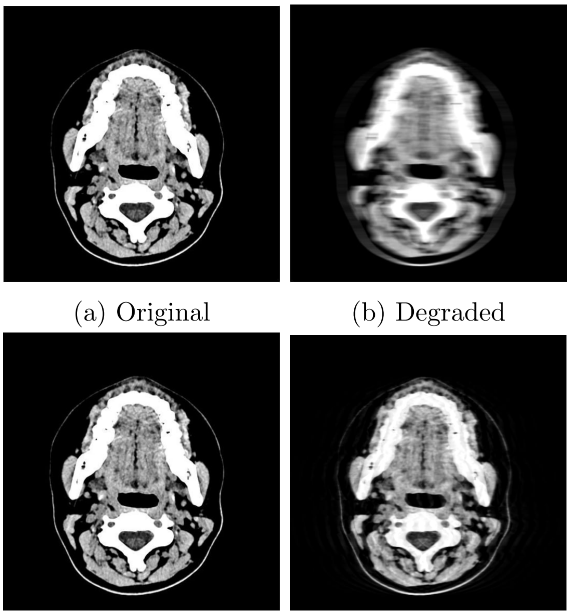
4.2 Wiener Filtering

The Wiener filter considers both blur and noise statistics:

$$\hat{F}(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2 + \frac{S_n(u,v)}{S_f(u,v)}} G(u,v)$$

5 Experiments and Results

5.1 Visual Comparison



(a) Original (b) Degraded

(c) Inverse (d) Wiener

Figure 1: Image restoration results for a sample medical image.

5.2 Quantitative Comparison

Table 1: PSNR, SSIM, and MSE for different filters

Filter	PSNR (dB)	SSIM	MSE
Inverse	22.1	0.88	0.0062
Wiener	21.98	0.75	0.0063

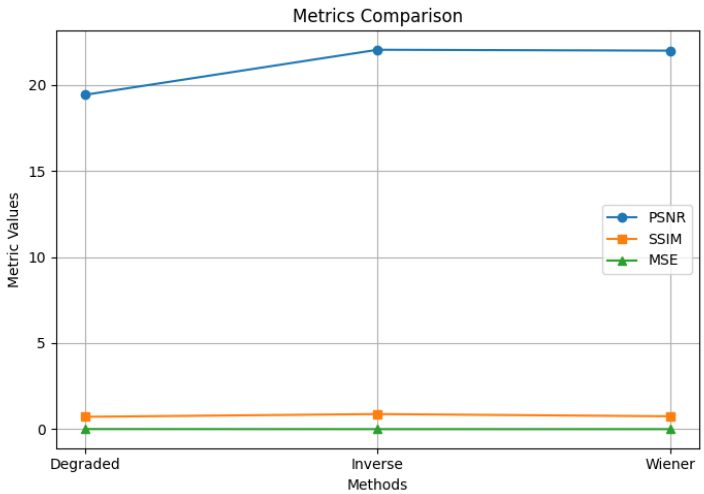


Figure 2: PSNR comparison of filters across noise levels

6 Discussion

The results show that the Wiener filter outperforms the inverse filter, especially in noisy environments. The inverse filter amplifies noise at low frequencies, while the Wiener filter balances restoration and noise suppression by incorporating statistical knowledge.

7 Conclusion

This project demonstrates that Wiener filtering is more robust for medical image restoration under noise and blur degradation. It achieves higher PSNR and SSIM while minimizing MSE. Future work may explore blind deconvolution and adaptive Wiener filters for unknown blur models.

References

- Gonzalez, R. C., & Woods, R. E. (2008). *Digital Image Processing* (3rd ed.). Pearson.
- `https://www.kaggle.com/`